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Employees' Satisfaction and Sentiment Analysis toward BERSATU Application

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Abstract: The era of digitalization has boosted companies to adopt innovative technology in seizing competitive superiority. However, adaptation to the change often deals with constraints, affecting operational efficiency and effectiveness. In this regard, PT Beiersdorf Indonesia faces issues regarding the impact of digital transformation of the sales process from manual to digital using Beiersdorf Sales Activity Tracking Routine (BERSATU) application, such as the difficulty of technology adaption by employees, accustomed to manual method, limitations of internet access in some areas, and technical constraints on application as well as insufficient technical support. Therefore, the research aims to analyze sentiment of user review on "BERSATU" application, using various algorithm classification and modeling topic. A total of 600 user reviews had been collected and analyzed to know positive or negative sentiments. Of 600 reviews, 60.33% was positive and 39.67% was negative. Based on the evaluated five algorithms classification, SVM and Naïve Bayes were superior with accuracy above 97% with better F1-Score. Regression Logistics had 96% accuracy, but it had low recall. Random Forest had 94% accuracy with a better F1-Score, but low recall was received. KNN has 93% accuracy, but low recall was obtained. SVM and Naïve Bayes were the recommended for further analysis. Modeling of LDA topics generated three topics with dominant keywords. Topic 1, such as "application," "bersatu," "data," "sales," and "results," covered 44.5% of the documents. Topic 2, including "application," "good," "visit," and "order," was relevant at 29.5%. Topic 3, comprising of "application," "assistance," "easy," "sell," and "store," was relevant 26.1% of the documents.

Keywords: Sentiment analysis, digital transformation, Beiersdorf sales activity tracking routine, sentiment classification, topic classification.

Introduction

PT Beiersdorf Indonesia is a company engaged in the skincare field, subsidiary of Beiersdorf AG, a multinational company having its primary office in Germany. Beiersdorf AG is well-known for famous brands, such as Nivea, Hansaplast, and Eucerin. PT Beiersdorf Indonesia is responsible for distribution and marketing of skincare products in Indonesia.

In addition, digital transformation has provided significant impact to individual, organizations, and systems in the last few years [1-3]. Organizations compete to innovate and adapt with increasingly sophisticated computing efficiency [4]. Digitalization then has boosted company to develop innovative technology and business models in seizing innovative superiority [5-7]. The Beiersdorf Sales Activity Tracking Routine (BERSATU) application is one of the efforts in digitizing the sales process at PT Beiersdorf Indonesia. The BERSATU application is designed for increasing efficiency by providing real-time monitoring and easy ordering. This system consists of two platforms, such as website and mobile application. The website allows sales supervisors to make efficient shop visit route for salesmen, while mobile application allows salesmen to make direct bookkeeping. Further, the application specially supports sales department, which consist of salesmen and sales supervisors.

Further, the introduction of this technology has been a challenge for employees to adapt, particularly those who are accustomed to work with manual methods. Some employees have difficulty using smartphones and websites, while limited internet access in some areas also hampers the use of applications, causing delays and inconveniences in managing customer orders. In addition, technical issues, such as application instability and lack of technical support from the company, cause difficulty for employees to complete tasks efficiently. These challenges reflect real barriers to changing the work culture from manual to digital sales processes, and it requires further efforts to support employee adoption of digital technologies and improve the quality and efficiency of existing applications. To provide a better understanding of these challenges, an analysis of respondent demographics and digital literacy levels provides valuable insights into how these factors influence user resistance.

Table 1. Age and digital literacy distribution

Region	Users	Age					Digital literacy		
		18-24	25-34	35-44	45-54	55+	Beginner	Intermediate	Advanced
West 1	280	56	84	70	42	28	84	140	56
West 2	24	5	7	6	4	2	7	12	5
Central	77	15	23	19	12	8	23	39	15
East	219	44	66	55	33	22	66	110	44

Table 1 reveals that employees with low computer literacy dealt with difficulty in adapting to new technology. Contrastingly, those having high digital literacy generally were more comfortable in navigating applications and assistant tools so that they experienced less constraints. Additionally, employees by age distribution also played an important role. Young employees, being an important part of the workforce, were usually easier to adapt to technological change than old employees, who required training and additional support for smooth transition to the digital process. The area with the concentrated young and highly digital literate employees was West 1 and East. They tended to deal with less adoption challenges. In contrast, the area, such as West 2, had few employees and many employees, who were unfamiliar with digital literacy, might experience more obstacles and required the targeted interventions. Responding to this gap was by customized training programs, better technical support, and ensuring stable application performance. They were significant to overcome obstacles and boost successful transition to digital workflow.

Historically, the application was launched at the beginning of 2023, and the review process was conducted between August 1-12, 2023, to evaluate its effectiveness by providing some months for user to adapt. As the passage of time, familiarity and skill with application increased, which had an impact on the quality of feedback. Employees, who had used application during such period, provided more informed opinions based on their experience, understanding of its features, limitations, and work impact. However, new users or inconsistent users had difficulty in adapting so that it resulted in feedback reflecting these challenges.

The research focuses on sentiment analysis to identify relationship between employees' assessment and the arising sentiments related adaptation to the BERSATU application. The sentiment analysis becomes essential tools to understand employees' response [8, 9], particularly considering adaptation challenge and technical constraints. Since the manual approach to sentiment analysis is complicated, time consuming and intensive resources [10, 11], the research employs algorithm of machine learning to automate and accelerate the classification process of sentiment so that it produces more accurate and efficient results. Algorithms, such as SVM, Naive Bayes, Random Forest, and Regression Logistics, are selected because they are proven effective in managing and analyzing sentiment data across multiple platforms.

Academically, Fransiska, S., *et al.* conducted analysis sentiment to service provider of by.U on Google Play Store. They applied TF-IDF and SVM methods in the classification process and obtained sufficient measurement results. Analysis results showed accurate and precise average, where recall and F1 scores were 84.7%, 84.9%, 84.7%, and 84.8%, respectively [12]. Styawati, *et al.* [13] used SVM algorithm to classify sentiment data across online applications. The result of the research demonstrated that Gojek was superior with 89% of the accuracy, 94% of the precision, 86% of the recall, and 90% of F1 score. Meanwhile, Grab obtained 87% of the accuracy, 94% of the precision, 85% of the recall, and 89% of F1 score. Pratmanto, *et al.* [14] conducted sentiment analysis on reviews of Shopee app on Google Play Store using Naive Bayes algorithm, and they achieved accuracy level of 96.667%. Oktaviani, *et al.* [15] applied Naive Bayes classifier and association methods to sentiment analysis on review of Traveloka e-commerce application on Google Play Store, and they reached accuracy level of 91.20%. Isnain and Kharisma [16], conducted sentiment analysis to review online learning using K-Nearest Neighbor (K-NN) algorithm. They found that the optimal testing with k1 score resulted in 84.65% of the accuracy. Masturoh, *et al.* [17] applied K-Nearest Neighbor (KNN) algorithm to analyze sentiment of e-wallet application, OVO, and they obtained maximal accuracy level by 84.86%. Warsito and Prahutama [18], conducted sentiment analysis in Tokopedia product online reviews using Random Forest algorithm and they achieve accuracy level at 97.38%. Mawardi and Darmaja [19] implemented Regression Logistics method to analyze sentiment on four social media apps on Google Play Store and they reached accuracy level by 81%. Sagala and Samuel [20] conducted sentiment analysis on review of ChatGPT app on Google Play Store utilizing a number of algorithms, including Random Forest, Support Vector Machine, and Naïve Bayes. The results of the study show that Random

Forest achieved an F1 score of 90% with 87.43% accuracy for positive review and 0.75% for negative review. Support Vector Machine also achieved a F1 score of 90% with 86.80% accuracy for positive review and 0.13% for negative review. Moreover, Naive Bayes obtained f1 score of 87%, with 88.06% accuracy for positive review and 0.12% for negative review.

The primary contribution of this research is as follows: Analysing employees' feelings, views, and experiences during the transition period from manual to digital sales processes. Evaluating five algorithm classifications, such as Support Vector Machine, Naive Bayes Classifier, Random Forest, Regression Logistics, and K- Nearest Neighbor, to determine its effectiveness in the sentiment analysis. Applying Latent Dirichlet Allocation to identify the recurring themes and topics in employees' sentiment.

The objectives of the research are to assist the company in understanding employees' sentiment toward the BERSATU application comprehensively. Then, the results of the analysis can expectedly provide outlook for PT Beiersdorf Indonesia in formulating a more comprehensive and effective strategy to increase technology acceptance and adaptation among employees.

Methods

Data Collection

The used data was users' rating and review of Beiersdorf Sales Activity Tracking Routine (BERSATU) application. This data was obtained through a questionnaire, distributed on August 1-12, 2023, via Google Form. A total of 600 users, either from website or by mobile versions, participated in filling questionnaire.

Dataset Pre-processing

The pre-processing stage aimed to list orderly organize raw data so that it was useful and efficient [21]. This stage included case folding, tokenization, stopwords deletion, and stemming [22]. Data validation and imputation were also performed to ensure data completeness and accuracy [23]. Following were the pre - processing stages, as follows. Case Folding: In the case folding procedure, words containing capital letter were changed into lowercase, while non-alphabetic characters were removed or treated as delimiter [24]. Tokenization: Tokenization used function of word_tokenize from the Natural Language Toolkit (NLTK) to split sentence becoming token pieces [25]. Stopwords Deletion: The stopwords deletion used a stopwords list in Bahasa Indonesia provided by NLTK. The words were deleted from the dataset because they had insignificant meaning [26]. Stemming: The stemming process employed the Sastrawi library to return the words having prefix or suffix to its word base or word root [27].

Data Labeling

The dataset that had through pre-processing categorized in accordance with the rating given in review [28]. In this research, the scale evaluation system was used to assist in sentiment classification. Employees' ranking was given numeric score, starting from 1 to 5. The threshold was set to differentiate between positive and negative sentiments. Specifically, reviews with rating above 3 were considered as positive sentiment, but reviews with rating below 4 were considered negative [29].

Word Cloud Visualization

The dataset that had been labeled were visualized using word clouds. Word clouds depicted frequently used words, with word size indicating its emergence frequency [30]. Visualization was shared into positive and negative sentiments.

Weighting (TF-IDF)

The dataset that has been labeled was processed using TF-IDF weighting method. In this stage, the frequently used words in documents (TF) and across the dataset (DF) were calculated. The DF score was used to calculate the Inverse Document Frequency (IDF), which was multiplied with TF score to produce TF- IDF score [31].

Classification of Sentiment Analysis

The weighted dataset was classified using five algorithms: Support Vector Machine (SVM), Naive Bayes Classifier, Random Forest, Logistic Regression, and K-Nearest Neighbor (KNN). This procedure involved the dataset partition into training data (80%) and testing data (20%) [32]. Then, the performance of the algorithms was assessed using standard classification evaluation matrix, such as accuracy, precision, recall, and F1-score [33].

Evaluation

Evaluation was conducted to assess the performance of classification model of machine learning. The approach used confusion matrix to provide outlook about accuracy, precision, recall, and f1-score of the model [34].

Topic Classification

Sentiment data was further analyzed using Latent Dirichlet Allocation (LDA) method to identify topics in review [35]. Modeling topic was separately conducted for both sentiment categories, such as positive and negative [36]. Data used at this stage was the same as the data used in the stage of sentiment classification analysis.

Results and Discussions

Questionnaire Results

Data for this research was collected from evaluation and user reviews to the BERSATU application. The data collection was conducted through the distributed questionnaires via Google Form, participated by 600 users documented in a spreadsheet. The rating scale ranged between score 1 and score 5, where score '1' indicated bad evaluation to the application and score '5' was good rating.

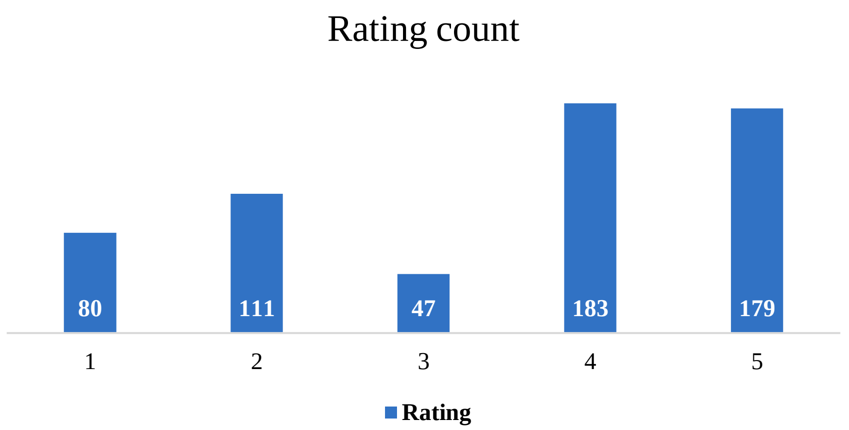

Figure 1. BERSATU app rating assessment

Figure 1 showed the distribution of user evaluation to the BERSATU application on the scale of 1 to 5, where '1' indicated a poor rating and '5' showed a good rating. Of 600 responding users, the majority provided score 4 or 5 for the application, where the total respondents were 183 and 179 users, respectively. It showed that more than 60% of users provided positive evaluation on this application, reflecting high-satisfaction level.

Contrastingly, 80 users provided with scores 1 and 111 gave scores 2, representing around 32% of the total respondents. It showed that most users stated their concern or dissatisfaction with the application. Meanwhile, 47 users provided score '3', which could be interpreted as neutral or moderate score.

In general, the results depicted that the BERSATU application was accepted by both users, although there was a segment, showing dissatisfaction. The contributing factors to a lower rating might include adaptation challenges with new applications, technical issues, or lack of utility for certain users. The findings highlighted the importance of further evaluation conducted on specific aspects of the application, having less utility for users. Moreover, understanding the low rating factor, developers could make the targeted improvements to increase users' future satisfaction.

Dataset Pre-processing Results

This section presents the results of the data preprocessing steps, including case folding, tokenization, stopword removal, and stemming. Each step is illustrated in the following tables, showcasing the transformations applied to the dataset.

Table 2. Case folding

Review Data	Case Folding
The application is good, but there are no store sales history menu, items sold	The application is good, but there are no store sales history menu items sold
Very practical to use for sales monitoring. However, the value updates H+1	very practical to use for sales monitoring however the value updates h1
Very Facilitating in the process of selling salesmen and monitoring salesman achievements for review and monitoring, attractive appearance and easy to use.	very facilitating in the process of selling salesmen and monitoring salesman achievements for review and monitoring attractive appearance and easy to use

Table 2 displayed the case folding process in data pre-processing, where all texts changed into lowercase to ensure analysis consistency. This step removed variation related uppercase-lowercase, such as 'the' and 'the' were treated as the same term. For example, "The application is good, but there is no sales store history" became "the application is good, but there is no sales store history", "Strongly helpful in salesmen' sales process" became "strongly helpful in salesmen' sales process". Case folding assisted to standardize text, which simplified further processing stage, such as tokenization and extraction features to improve accuracy and efficiency of sentiment analysis.

Table 3. Tokenization

Case Folding	Tokenization
the application is good but there are no store sales history menu items sold	the, application, is, good, but, there, are, no, store, sales, history, menu, items, sold
very practical to use for sales monitoring however the value updates h1	very, practical, to, use, for, sales, monitoring, however, the, value, updates, h1
very facilitating in the process of selling salesmen and monitoring salesman achievements for review and monitoring attractive appearance and easy to use	very, facilitating, in, the, process, of, selling, salesmen, and, monitoring, salesman, achievements, for, review, and, monitoring, attractive, appearance, and, easy, to, use

Furthermore, Table 3 shows the tokenization process, a fundamental stage in the text pre-processing, where sentences splat down into some words or tokens to facilitate further analysis. As example, "the application is good, but there is no menu item of sales store history" into "the", "application", "are", "good", "but", "there" , "is", "no", "menu", "item", "of", "sales", "store", "history". Tokenization allowed every word to be analyzed in an independent measure, prepared text for stopwords deletion and stemming stages.

Table 4. Stopwords removal

Tokenization	Stopwords removal
the, application, is, good, but, there, are, no, store, sales, history, menu, items, sold	application, good, store, sales, history, menu, items, sold
very, practical, to, use, for, sales, monitoring, however, the, value, updates, h1	practical, sales, monitoring, value, updates, h1
very, facilitating, in, the, process, of, selling, salesmen, and, monitoring, salesman, achievements, for, review, and, monitoring, attractive, appearance, and, easy, to, use	facilitating, process, selling, salesmen, monitoring, achievements, review attractive, appearance, easy, use

Table 4 demonstrates the stopwords deletion process, which removed common words with low analytical score, such as "the", "is", and "but". This step only left meaningful words, such as "application", "good", "sales", "store", "history", "menu", "item", "sold", so the dataset became more focused and relevant. The stopwords deletion reduced noise and improved computing efficiency by narrowing down the words that directly contributed to the analysis.

Table 5. Stemming

Stopwords Removal	Stemming
application, good, store, sales, history, menu, items, sold	application, good, store, sales, history, menu, item, sold
practical, sales, monitoring, value, updates, h1	practical, sales, monitor, value, update, h1
facilitating, process, selling, salesmen, monitoring, achievements, review, attractive, appearance, easy, use	facilitate, process, sell, salesmen, monitor, achievement, review, attractive, appearance, easy, use

Additionally, Table 5 displays stemming stage, where the words were reduced from their base word to ensure consistency throughout variations of the same word. For examples: 'facilitate' became 'facilitate' and 'supervise' became 'monitor'. By consolidating various word forms into one representation, stemming stage assisted to increase consistency of textual data, simplify analysis, and reduce redundancy.

Data Labeling Results

The pre-processing was performed on data review to clear and prepare text. Subsequently, the following stage was to classify every review into positive or negative sentiment based on rating score. The positive sentiment was put in review with a rating score 4 or 5, while the negative sentiment was given in review with rating score 1, 2, or 3.

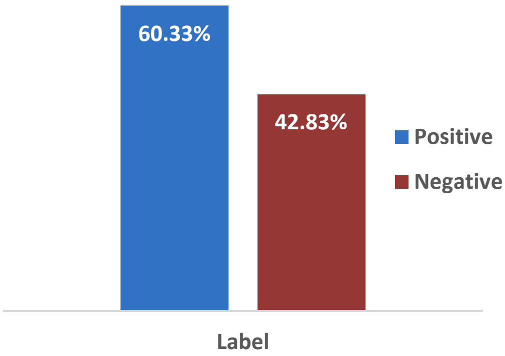

Figure 2. Sentiment class graph of BERSATU app user reviews

Figure 2 illustrates the distribution of user reviews, categorized into positive and negative sentiment classes for the BERSATU application. In the analysis, the users rating 4 or 5 was classified as positive, while rating 1, 2, or 3 was classified as negative. The classification approach was intended to catch users' sentiment about this application, where higher rating showed more satisfaction and lower rating was reflected dissatisfaction.

Chart described that 60.33% of reviews included the category of positive sentiment. It indicated that most users had good view to the application. The class of positive sentiment, contributing more than half of the reviews, demonstrated that general users were satisfied with features, utilities, or performance of the application.

In contrary, 39.67% of the reviews classified as negative sentiment, highlighting that most of the users stated dissatisfaction or experienced issues with the application. The percentage of highly negative feedback showed potential areas for improvements, such as utility issues, technical difficulty, or non-satisfied user expectation.

The distribution between positive and negative sentiments in the analysis provided valuable insights for developers and stakeholders. The substantial positive sentiment reflected firm foundation from users' consent; however, the presence of a prominent negative sentiment also indicated the required attention to specific issue that could increase users' experience and satisfaction.

Word Cloud Visualization Results

The data labeling process was conducted to classify reviews into positive and negative sentiments. The following stage was to visualize the result. Word Cloud was used as effective visual tools to illustrate frequently used words appearing in every sentiment category. Then, the objective of this stage was to identify trends, focus on key themes in reviews, and provide additional outlook regarding users' sentiment to the BERSATU application. The class of positive sentiment was depicted in Figure 3 and the class of negative sentiment was in Figure 4.

Figure 3. Word cloud of positive sentiment class of BERSATU app

Figure 4. Word cloud of negative sentiment class of BERSATU app

Weighting Results (TF-IDF)

TF-IDF combined the concept of TF (Term Frequency, measuring how often a word appeared in a document) and IDF (Inverse Document Frequency, assessing how often or rare a word appeared in a cluster of documents) to provide appropriate weight for every word in a document. The purpose was to recognize the most significant and important words in a document so that it provided better and in-depth understanding about its contents.

```
(0, 171)      0.3205362499258052
(0, 626)      0.6697971754507113
(0, 184)      0.6697971754507113
(2, 590)      0.17428970411503664
(2, 595)      0.14172757029244593
(2, 396)      0.09578205197566896
(2, 415)      0.16375075186099092
(2, 323)      0.3485794082300733
(2, 471)      0.17428970411503664
(2, 106)      0.17428970411503664
(2, 334)      0.15047324227667241
```

Figure 5. TF-IDF process result

The TF-IDF representation results were shown as a matrix that presented weighing in certain documents sequentially as seen in Figure 5. As example, in the first line (0, 171), the number 0 indicated row index number, and 171 indicated column index number. It shows that words with 171 indexes had significant weight in the document.

Sentiment Classification Results

The results of sentiment classification analysis described that the classification of sentiment model used machine learning algorithm for the class both positive and negative sentiments. Table 5, describing accuracy comparison, depicted that SVM and Naive Bayes methods had the highest accuracy, such as 97%, which indicated excellent ability to classify all data correctly. Precision measuring true-positive prediction also showed positive results. SVM, Naive Bayes, and Regression Logistics highlighted high precision for the class of positive sentiment. SVM and Naive Bayes achieved 96% of the precision, and the class of negative sentiment had 97% of the precision. Meanwhile, Regression Logistics reached 95%.

Table 6. Algorithm performance comparison

Algorithm	Accuracy	Precision		Recall		F1-Score	
		+	-	+	-	+	-
SVM	97%	96%	98%	99%	93%	97%	95%
Naive Bayes	97%	97%	96%	97%	96%	97%	96%
Logistic Regression	96%	95%	98%	99%	91%	97%	94%
Random Forest	95%	95%	95%	97%	91%	96%	93%
KNN	93%	93%	91%	95%	89%	94%	90%

When assessing performance comprehensively, SVM and Naive Bayes were consistent to perform other algorithms, such as Regression Logistic, Random Forest, and K-Nearest Neighbor (KNN), showing more reliable and superior prediction ability, which might be caused by the characteristics and quality of the used data. SVM was superior in recall rate, reaching 98% for the detection of positive sentiment, and 97% for the detection of negative sentiment. Naive Bayes also well-performed, with recall rate above 96% for the positive sentiment and 98% for the negative sentiment. The F1 score, which reflected balance between precision and recall, had a firm performance, where F1 score of SVM achieved 95% and Naive Bayes had a slightly higher F1 score, such as 96%.

Further, the confusion matrix analysis provided a better understanding regarding the classification strength of each model and improvement area. For the SVM model, shown in Figure 6, this model had succeeded in classifying 74 cases as positive (True-Positive) and 42 cases as negative (True-Negative), which indicated strong ability to identify both classes of sentiment correctly. However, there WAs a few error classification, where 1 case was misclassified as positive (False-Positive) and 3 cases were misclassified as negative, whereas it was positive (False-Negative).

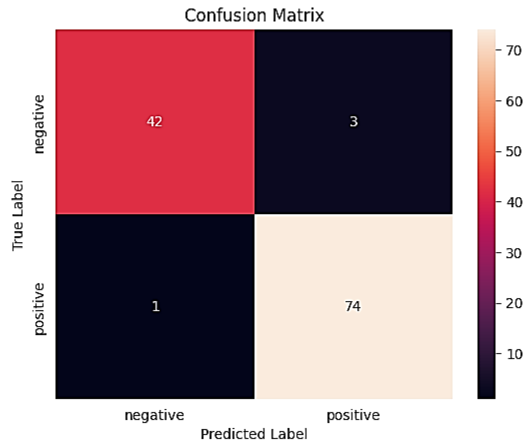

Figure 6. Confusion matrix for SVM

The Naïve Bayes model, shown in Figure 7, classified 73 cases correctly as positive (True-Positive) and 43 cases were negative (True-Negative). The model showed a little difference in error classification pattern, where 2 cases were false-positive, and 2 cases were false-negative. Although the error classification was minimal, it provided an outlook about ambiguous case management by the model.

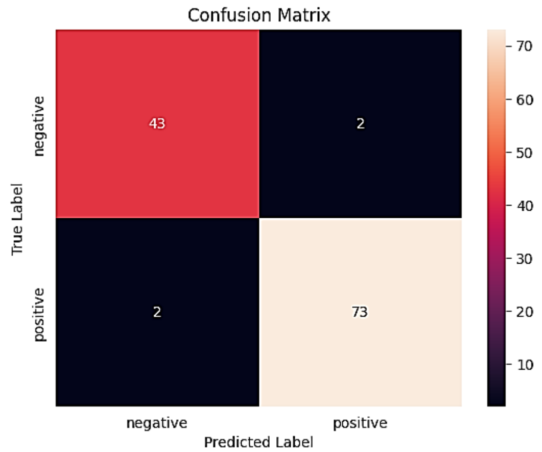

Figure 7. Confusion matrix for Naïve Bayes

The confusion matrix on both models highlighted their reliable performance in the classification of sentiment. The Naïve Bayes depicted a slightly better balance in the matrix of F1 score. This result described that though both models suited perfectly for the sentiment analysis, it might offer a little profit in the balanced accuracy aspect across the classification of positive and negative sentiment.

Classification Results Topics

The implementation of the Latent Dirichlet Allocation (LDA) model on the matrix of terms-documents described three identified topics in terms of application reviews. Table 6 showed that the LDA model was trained with 50 iterations to obtain more insight from the data. Through the show_ topics ( ) method in the LDA model, a keyword that represents every topic could be displayed. This assisted in understanding the essence of every topic, which included various aspects and features of the application.

Table 7. Topic results and keywords

Topic	Keyword Set
1	(0.081*"application" + 0.056*"bersatu" + 0.051*"not" + 0.051*"make" + 0.029*"data" + 0.027*"really" + 0.026*"web" + 0.024*"sales" + 0.023*"result" + 0.017*"salesman")
2	(0.084*"application" + 0.056*"bersatu" + 0.044*"like" + 0.041*"make" + 0.033*"visit" + 0.027*"error" + 0.024*"good" + 0.023*"upload" + 0.023*"order" + 0.021*"not")
3	(0.077*"application" + 0.047*"help" + 0.033*"easy" + 0.033*"sell" + 0.030*"shop" + 0.020*"work" + 0.020*"report" + 0.017*"visit" + 0.014*"bersatu" + 0.014*"salesman")

Visual representation of the topics was displayed in the bubble diagram, where the size of every bubble was in accordance with the importance of the topics in corpus, entirely. Bigger bubbles demonstrated frequently appeared topics in all user reviews. The layout of bubbles reflected different characteristics from every topic, where the calculated coordinates were based on score weight related to every topic. On the left side of visualization, bar chart highlighted the most relevant words for every topic, providing clearer views on the keywords that drove every sentiment (Figure 8-11).

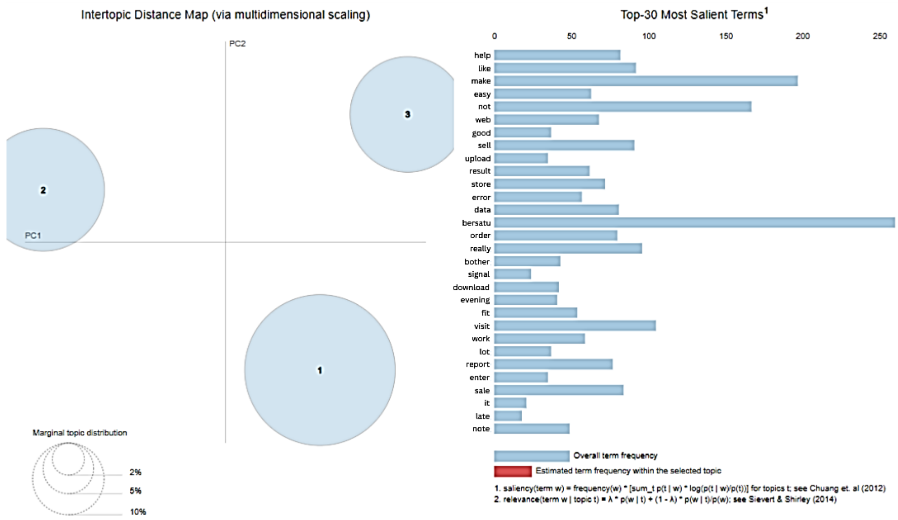

Figure 8. Intertopic distance map overall topic

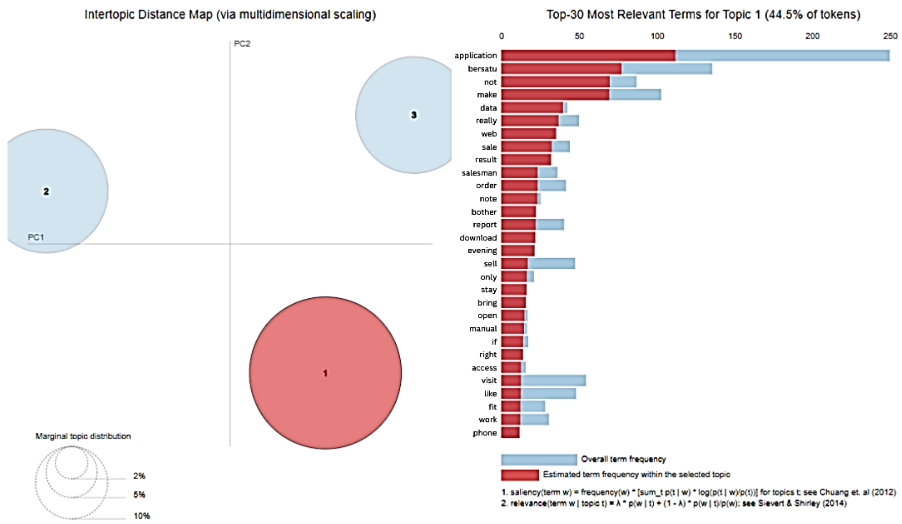

Figure 9. Intertopic distance map overall topic 1

Keywords such as 'application', 'better', 'visit', and 'order' dominated Topic Two, indicated by the highlighted words in a bar chart and showed positive sentiment related to users' experience. The keywords depicted that users were satisfied with certain feature applications, especially those simplifying the visiting and booking processes so that it increased operational efficiency. The visualization affirmed positive sentiment by illustrating the superiority of these words, which showed that the BERSATU application effectively satisfied the need of users in this area.

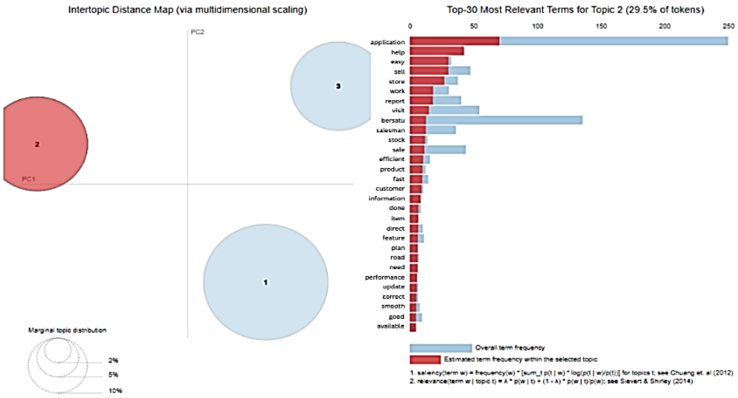

Figure 10. Intertopic distance map overall topic 2

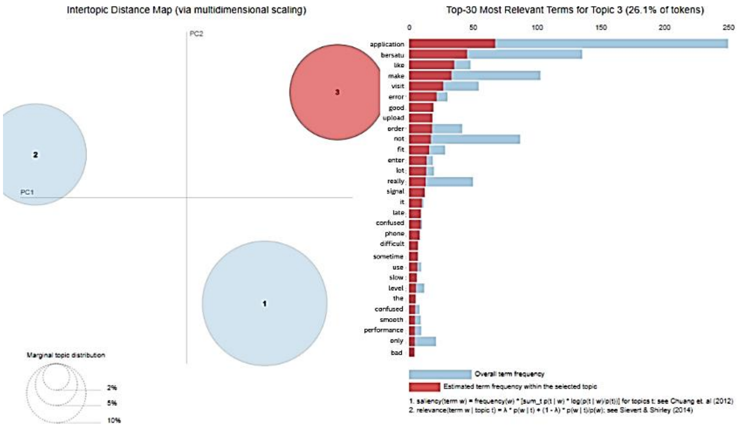

Figure 11. Intertopic distance map overall topic 3

On Topic Three, keywords, such as 'use', 'assist', 'easy', 'sell', and 'shop' indicated neutral sentiment, shown in the bar chart. Although users' convenience was mentioned, this topic, especially about basic operational aspect, displayed strong dissatisfaction expression. This neutral tone was reflected in the size of bubbles, showing that the application provided sufficient support for any tasks, such as sales and product stock management, but a typical element was none that it led to a more positive or negative response from the users.

Topic One was characterized by keywords such as 'no', 'create', 'data', and 'result', which was visually superior in a bar chart and showed technical issues in the application. The negative sentiment reflected users' dissatisfaction, particularly regarding insufficient technical stability and support, which affected operational efficiency. Moreover, visualization depicted these keywords as the core of Topic One, which highlighted the need of accuracy and reliability increasing in data processing because it had negative impact on users' experience.

Conclusions

The research has revealed the detailed sentiment analysis regarding the evaluation of employee's response toward the BERSATU application at PT Beiersdorf Indonesia. Based on the tested classifiers, Support Vector Machine (SVM) and Naive Bayes have been proven to be the most effective, where each achieves 97% of the accuracy level. This high performance describes that these algorithms have been suitable to classify employees' sentiment accurately in the dataset. Of 600 reviews, the sentiment distribution shows that 60.33% has been positive and 39.67% has been negative, highlighting satisfaction and required improvement areas.

The use of Latent Dirichlet Allocation (LDA) in this research has identified three key themes in employees' feedback, such as utility, technical challenges, and improvement suggestion issues. The themes provide comprehensive understanding regarding an employee's experience with the related application. The utility issue reflects adaptation challenges dealt by some employees, while technical challenges highlight stability and infrastructure areas that require improvement. Suggestions indicate that employees involved actively and provided valuable feedbacks to increase application performance.

The insight proposes practical benefit for the management of PT Beiersdorf Indonesia. Focusing on the identified topics, the company can target specific improvements to the BERSATU application, simplify employees' support programs, and enhance digital adaptation strategies. The implementation of these can ultimately increase employees' satisfaction, improve operational efficiency, and support successful and smooth digital transformation in the organization.

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